Gabor Filters for Rotation Invariant Texture Classification

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Abstract - **A Gabor filter based feature extraction scheme for texture classification is proposed. By using a novel set of circularly symmetric filters, rotation invariance is achieved. The scheme offers a high classification performance on textures at any orientation using both fewer features and a smaller area of analysis than most existing schemes. The performance of the scheme on noisy images is also investigated, demonstrating a high robustness to noise.**

I. Introduction

Texture is a common component in the majority of natural images. Texture analysis is therefore an important stage of many image processing applications. These applications range from remote sensing and crop classification to the segmentation and interpretation of medical images. The analysis and synthesis of texture also play an important role in second generation image coding techniques. A variety of texture analysis techniques have been proposed over recent years. Stochastic models such as GMRFs and autoregression [1,2], spatial-frequency based techniques including wavelets [2,3,4,5] and Gabor filters [6] and statistical analysis methods [7] have all been considered. Spatial-frequency techniques are particularly amenable to texture analysis as they can accurately identify the periodicity inherent in most textures and are thus similar to the human visual system. They also perform well on textures of a more random nature by characterising the texture's scale and are therefore applicable to any kind of texture analysis.

Existing texture analysis schemes tend to suffer from a number of drawbacks. Many schemes use an excessively large number of features to represent the texture [7,8]. This results in a large amount of computation each time an unknown texture is classified. For example, Lam and Li use 18 features to achieve a 92.4% accuracy in [8] and claim that more features are usually necessary in other existing schemes. Furthermore, a large image area is often required to perform the texture analysis. It is common for a 256x256 area to be used [5]. Although a high level of classification accuracy is easily achieved when a large image area is used, such large image samples are usually either unavailable or impractical. Therefore, it is preferable that a texture be classified from a smaller sample, especially if the texture analysis is to be used in an image segmentation problem where high resolution is required.

Another drawback of the majority of texture classification schemes is their inability to maintain a high classification performance when the textures for classification have undergone a rotation [4] or contain noise. Most schemes require that the textures being classified are at the same orientation as those in the training set. This is a severe limitation since the angle that a texture appears at is usually unpredictable.

Here, a spatial-frequency based feature extraction scheme is proposed. This scheme uses a novel approach based on Gabor filtering to extract rotation invariant features for texture classification. The scheme extracts just four features from a small (16x16) image sample, but achieves a high level of classification accuracy. It is also shown to have a high invariance to noise.

II. Feature Extraction

Gabor filters are often used in texture analysis to provide features for texture classification and segmentation. The Gabor filter takes the form of a 2-D

Gaussian modulated complex sinusoidal grating in the spatial domain [6]:

$$h(x,y) = g(x',y').e^{-2\pi j(Ux+Vy)} \tag{1}$$

where (U,V) defines the position of the filter in the Fourier domain with a centre frequency of $F=\sqrt{U^2+V^2}$ and an orientation of $\theta = \arctan(V/U)$. The term $g(x',y')$ represents a Gaussian function orientated at an angle ϕ, where (x',y') are the rotated co-ordinates given by $x' = x\cos\phi + y\sin\phi$ and $y' = -x\sin\phi + y\cos\phi$. The general form of the Gaussian function is:

$$g(x,y) = \left(\frac{1}{2\pi\lambda\sigma^2}\right).e^{-\left[\frac{(x/\lambda)^2+y^2}{2\sigma^2}\right]} \tag{2}$$

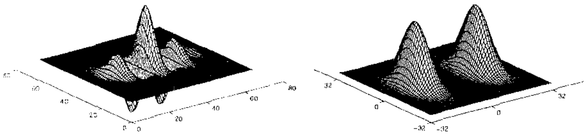
where λ defines the aspect ratio and σ the scale factor. The scale factor is typically determined by the centre frequency of the filter such that high frequency filters are more localised in space, i.e.

$$\sigma = \mu / F \tag{3}$$

where μ is a constant. An example of a Gabor filter in both spatial and Fourier domains is given in Fig. 1. A fixed set of filters are usually chosen to generate features for texture classification, centred at the required frequencies and orientations to obtain the optimum coverage of the Fourier domain.

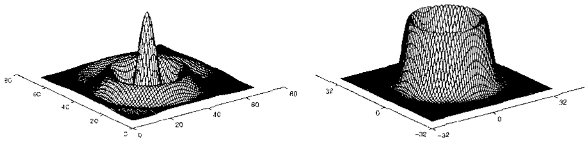
The sinusoidal grating of the Gabor filter varies in only one direction thus making it highly orientation specific. Therefore, the filter is very effective at orientation dependent texture analysis but is not suitable for rotation invariant texture classification. In order for the filter to be rotation invariant, it is necessary that the sinusoidal grating varies in all directions. Hence, in the proposed approach, the filter is made circularly symmetric to achieve rotation invariance. This filter is again formed by modulating a complex sinusoidal grating with a Gaussian function. However, both the Gaussian and the grating vary only in a radial direction from the origin, such that the filter is completely circularly symmetric. The circularly symmetric Gabor filter is given by:

$$h(x,y) = g(x,y).e^{-2\pi jF\sqrt{x^2+y^2}} \tag{4}$$



(a) (b)

Fig. 1. Traditional Gabor filter with F=16 cycles/image and λ=0.5 shown in (a) spatial and (b) Fourier domain.



(a) (b)

Fig. 2. Circularly symmetric Gabor filter with F=16 cycles/image shown in (a) spatial and (b) Fourier domain.

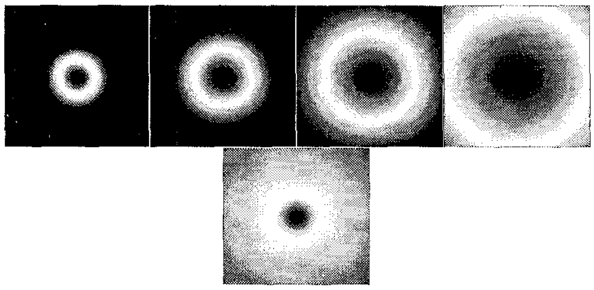


Fig. 3. Fourier domain representation of the set of circularly symmetric Gabor filters used, and their sum, with F=2.0, 3.17, 5.04 and 8.0 cycles/image for a 16x16 image.

where F is the required centre frequency. In this case it is unnecessary to rotate the co-ordinates of the Gaussian since it is circularly symmetric. The Gaussian is given by:

$$g(x,y) = \left(\frac{1}{2\pi\sigma^2}\right).e^{-\left[\frac{x^2+y^2}{2\sigma^2}\right]} \tag{5}$$

An example of a circularly symmetric Gabor filter is shown in Fig. 2.

To extract texture-based features from an image using the circularly symmetric filters, four filters are used, spaced in geometric progression across the Fourier domain to achieve optimum coverage. These filters and their sum are represented by intensity in the Fourier domain in Fig. 3. It can be seen that the bandwidth of each filter increases with frequency (as determined by the scale factor, σ in eqn. 3). μ has been chosen such that the filters overlap slightly and the Fourier domain is as evenly covered as possible. However, the very low frequencies are not covered, since these convey little textural information about the image (only gradual changes in grey level). The feature extraction process involves filtering the image with each of the four filters and then measuring each filter's response to the image. In this method, the mean absolute deviation from the mean for each filtered image is used:

$$f = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} \left| x_{i,j} - \bar{x} \right| \qquad (6)$$

where $\bar{x}$ is the mean of the filtered image and M and N are its dimensions. f is calculated for each filtered image to provide four rotation invariant features.

III. Classification Results

Sixteen 256x256 textures from the Brodatz album [9] were used to test the performance of the proposed scheme. Samples of these textures are shown in Fig. 4. A sample image of each texture was used to provide a training set of 16x16 sub-images. These textures were presented at angles of 0°, 30°, 45° and 60° in order to train the classification algorithm. A further 7 sample images of each texture were presented to the algorithm as unknown textures for classification. The textures were classified at angles of 20°, 70°, 90°, 120°, 135° and 150°. A minimum distance classifier using the Mahalonobis distance [5] was employed to perform the classification.

The circularly symmetric Gabor filters gave a classification accuracy of 95.4% across the 672 samples, as illustrated in the confusion matrix in Table 1. This compares very favourably with existing texture classification schemes particularly when considering the smaller image area and fewer features used here. It is comparable to the wavelet and GMRF based schemes presented in [2] and [10]. The advantage of the Gabor filter based scheme is that the filters can easily be tuned to different scales of texture if necessary (although the current choice of filters cover a wide range of scale for the textures being classified, see Fig. 4). Table 1 indicates that the majority of misclassifications occur due to matting and raffia being mistaken for rattan. This is due to the relationship between the spatial frequencies of these textures: raffia and matting have approximately twice the spatial frequency of rattan and thus have large components at the same frequency as rattan, as well as at their own higher frequencies. Misclassifications such as these are to be expected when such a large database of textures is used.

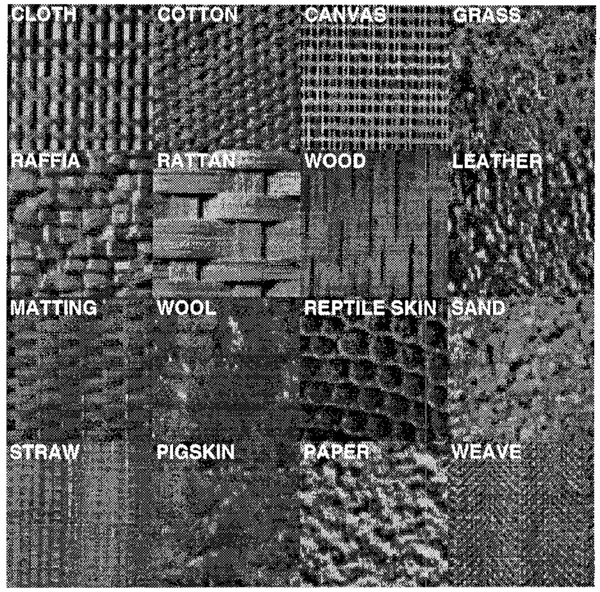


Fig. 4. The 16 textures used to test the performance of the circularly symmetric Gabor filters.

TABLE I
CONFUSION MATRIX FOR CIRCULARLY SYMMETRIC GABOR FILTERS IN CLASSIFICATION OF ROTATED TEXTURES

	CLOTH	COTTON	CANVAS	GRASS	RAFFIA	RATTAN	WOOD	LEATHER	MATTING	WOOL	REPTILE	SAND	STRAW	PIGSKIN	PAPER	WEAVE
CLOTH	42															
COTTON		42														
CANVAS			42													
GRASS				42												
RAFFIA					24	17						1				
RATTAN						42										
WOOD							42									
LEATHER								42								
MATTING						12			29		1					
WOOL										42						
REPTILE											42					
SAND												42				
STRAW													42			
PIGSKIN														42		
PAPER															42	
WEAVE																42
CLASSIFICATION ACCURACY: 95.4%																

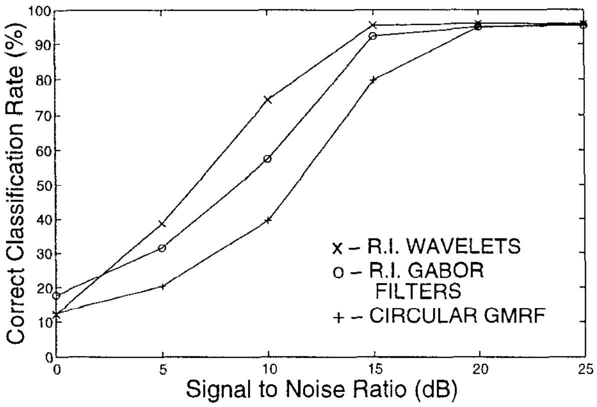


Fig. 5. Noise performance of the rotation invariant Gabor filters compared to two other rotation invariant schemes.

IV. Noise Performance

It is important that any texture classification scheme can operate successfully in a noisy environment. Noise is common in real images due to imperfections in the imaging process or a noisy communications link. The performance of the circularly symmetric Gabor filters on noisy images was tested by introducing various levels of additive white Gaussian noise to each texture and compared with our schemes proposed in [2] and [10]. The noise was added with zero mean and a variance dependent on the required signal-to-noise ratio which ranged from a barely visible 25dB to a very obvious 0dB.

The noise performance of the circularly symmetric Gabor filters is shown in Fig. 5. The classification accuracy degrades gracefully with increasing noise as expected. It can be seen that the Gabor filters outperform the previously proposed circular GMRF approach [2,10] but cannot quite match that of the rotation invariant wavelet-based approach [2,10]. Nevertheless, the proposed scheme is robust down to a signal-to-noise ratio of 15dB.

V. Conclusions

A novel texture classification scheme based on Gabor filters has been proposed. Unlike traditional Gabor filters, the filters in the proposed approach are circularly symmetric, thus providing rotation invariant features. The proposed scheme has been shown to give a high level of accuracy in the classification of rotated textures. Furthermore, the scheme uses significantly fewer features than most existing schemes resulting in fast and simple classification. The scheme also operates on a relatively small image area, yielding a larger number of applications with a lower computational complexity than existing schemes. The scheme's robustness to noise has been shown to be adequate for most image processing applications. Further information will be published in [11].

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